The Soft-Output Principle – Reminiscences and New Developments

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Dedicated to Prof. Dr.-Ing. Dr.-Ing. E. h. Joachim Hagenauer on the Occasion of his 65th Birthday

SUMMARY

A major breakthrough in digital communications was the provisioning of "soft" outputs at each processing stage, with appropriate capabilities to use this as soft inputs in the next processing stage. This allowed for much more performant receivers especially in difficult mobile radio channel conditions, and set the stage for iterative processing. This article will outline the development of soft output algorithms over the last two decades along with associated state-of-the-art applications and conclude with an outlook towards novel applications of the soft principle.

1 Introduction

Let us assume that the weather is a binary, uniformly distributed random variable taking the events "sunny" and "rainy", respectively. Let us further assume two unbiased and honest weather stations making observations to predict the weather for the same location. Both weather stations are assumed to use different measurement principles, and hence their errors are statistically independent. For example, the first weather station (WS 1) may observe the colour of the sunsets and the second (WS 2) may use sophisticated weather satellites. Suppose that WS 1 predicts a 60 % chance for sunny weather, whereas WS 2 predicts a 70 % chance for sunny weather. The ultimate question, called *weather problem* [1], is: What is the probability for sunny weather given both observations? Can you imagine that the correct solution is 77.7 % (given that a-priori both possible outcomes are equally likely)? Has understanding the weather problem any stimulating effect on modern communication and navigation systems? The principle behind the weather problem is the central element of information combining, a concept which has significant impact on iterative processing as, for example, applied in turbo decoding.

In soft-input decoding (traditionally called soft-decision decoding), a channel decoder benefits by accepting real-valued inputs (i.e., soft inputs). For example, the Viterbi algorithm is capable of making benefit of soft inputs [2]. However, the Viterbi algorithm outputs integer values (i.e., hard outputs). No reliability information about the output symbols is available. Hence, in the next processing stage only hard inputs are available. Much work in the formulation of soft *output* algorithms was, in fact, motivated by the desire to provide soft *inputs* to the next processing stage. For instance, a channel equaliser should generate soft outputs so as to improve the efficiency of a subsequent soft-input channel decoder.

The first step in the evolution was the invention of *soft-input soft-output* algorithms ("don't make hard decisions"). Examples include the Bahl-Cocke-Jelinek-Raviv (BCJR) algorithm [3], soft-input soft-output algorithms by Battail [4] and Huber [5], and the Soft-Output Viterbi Algorithm (SOVA) by J. Hagenauer and P. Hoeher [6],

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which has later been recognised as an approximation of the BCJR algorithm [7]. This class of algorithms delivers symbol-by-symbol a-posteriori probabilities or approximations thereof. An alternative are list-output algorithms, providing an ordered list of the N most likely paths [8], or generalisations thereof. In the sequel, we will focus on symbol-by-symbol soft-output algorithms.

The second step of the evolution was the *combination of soft outputs* from different processors. Given the interpretation that the SOVA is a nonlinear digital filter which is able to improve the signal-to-noise ratio [6], reliability-based iterative decoding of parallel concatenated codes [9] and block/convolutional product codes [10] (which may be seen as serially concatenated codes) was proposed at the same time. The major contribution of these early turbo processing papers was the step from *soft* to *iteration*. To successfully reach that goal, the main operation is *information combining* [11], i.e., the combination of several soft values taking a-priori information into account. As we saw above, proper information combining is the clue for solving the weather problem. When applied to iterative decoding we also need to include the concept of *extrinsic information* [9] to ensure that information should be used only once during information combining. (The exchange of extrinsic soft values is called "partial factor MAP filtering" in [10].)

The remainder of this article is as follows: In Section 2 basic operations of soft values in form of log-likelihood ratios are presented. Sections 3 to 7 cover state-of-the-art applications, where log-likelihood values and soft processing are used. Finally, we conclude with an outlook to novel applications.

2 Log-Likelihood Algebra

Log-Likelihood Ratio The *log-likelihood ratio* of a binary random variable X with elements $x \in \{+1, -1\}$ given an observation y is defined as

$$L(X|y) := \log \frac{P(X=+1|y)}{P(X=-1|y)}. \tag{1}$$

$P(X=x|y)$ denotes the probability that the random variable X takes on the value x given the observation y, and $+1$ is the identity element under the $\oplus$ addition. The log-likelihood ratio $L(X|y)$ will be denoted as the L-value of the random variable X given y. The sign of $L(X|y)$ is the hard decision and the magnitude $|L(X|y)|$ is the reliability of this decision. Unless stated otherwise, the logarithm is the natural logarithm. We immediately obtain that

$$\begin{aligned} L(X|y) &= \log \frac{P(X=+1)}{P(X=-1)} + \log \frac{P(y|X=+1)}{P(y|X=-1)} \\ &:= L(X) + L(y|X) \end{aligned} \tag{2}$$

$L(X)$ and $L(X|y)$ are called a-priori and a-posteriori log-likelihood ratio, respectively. It can also be shown that

$$\begin{aligned} L(X|y_1,y_2) &:= \log \frac{P(X=+1|y_1,y_2)}{P(X=-1|y_1,y_2)} \\ &= L(y_1|X) + L(y_2|X) + L(X) \\ &= L(X|y_1) + L(X|y_2) - L(X). \end{aligned} \tag{3}$$

This generalisation of (2) is the main recipe for solving the weather problem: Given the specific numbers stated in the introduction, we obtain that $L(X|y_1) = \log\frac{0.6}{0.4}$, $L(X|y_2) = \log\frac{0.7}{0.3}$, and $L(X) = 0$. Hence, $L(X|y_1,y_2) = \log\frac{0.6}{0.4} + \log\frac{0.7}{0.3}$. Upon substitution into

$$P(X=+1|y_1,y_2) = \frac{e^{L(X|y_1,y_2)}}{1+e^{L(X|y_1,y_2)}}, \tag{4}$$

the perhaps surprising result of 77.7 % is obtained.

The remaining formulas of this section apply to a-priori as well as a-posteriori log-likelihood ratios.

"Soft Bits" We now view X simultaneously in GF(2) and as real number. Then $X_1 \oplus X_2$ corresponds to $X_1 \cdot X_2$. With

$$\begin{aligned} \lambda(X) &:= \mathrm{E}\{X\} = (+1)\frac{e^{+L(X)}}{1+e^{+L(X)}} + (-1)\frac{e^{-L(X)}}{1+e^{-L(X)}} \\ &= \tanh(L(X)/2), \end{aligned} \tag{5}$$

we have the so-called *soft bit* [12], ranging from -1 to $+1$.

Addition of "Soft Bits" For the addition of two statistically independent random variables X_1 and X_2 in GF(2),

$$X_3 = X_1 \oplus X_2, \tag{6}$$

for the corresponding "soft bits" we obtain

$$\lambda(X_3) = \lambda(X_1) \cdot \lambda(X_2), \tag{7}$$

when using the real number operation $E\{X_1 \cdot X_2\} = E\{X_1\} \cdot E\{X_2\}$. Here the multiplication has to be performed over the real numbers. Using L-values we obtain

$$\begin{aligned} &L(X_1 \oplus X_2) \\ &\quad= \log \frac{1+e^{L(X_1)}e^{L(X_2)}}{e^{L(X_1)}+e^{L(X_2)}} \\ &\quad= 2\,\mathrm{atanh}(\tanh(L(X_1)/2)\cdot\tanh(L(X_2)/2)), \\ &\quad\approx \mathrm{sign}(L(X_1))\cdot\mathrm{sign}(L(X_2))\cdot\min(|L(X_1)|,|L(X_2)|) \end{aligned} \tag{8}$$

where the "box-plus" symbol $\boxplus$ is defined as

$$L(X_1) \boxplus L(X_2) \triangleq L(X_1 \oplus X_2), \tag{9}$$

for abbreviation [12]. The reliability of the sum $\boxplus$ is therefore dominated by the smallest reliability of the terms.

If multiplication is inconvenient one can alternatively operate in the log-domain:

$$\Lambda(X) := -\log(|\lambda(X)|) = -\log(|\tanh(L(X)/2)|). \tag{10}$$

Inversely, one has

$$|\lambda(X)| = e^{-\Lambda(X)}. \tag{11}$$

Hence, we get a simple addition of real positive numbers for the relation of the magnitude

$$\Lambda(X_3 = X_1 \oplus X_2) = \Lambda(X_1) + \Lambda(X_2), \tag{12}$$

and we obtain the sign of the soft-output by $X_1 \cdot X_2$. We want to emphasise that for the transformation from $|L|$ to Λ and vice versa the same function

$$f(a) = \log \frac{1+\exp(-a)}{1-\exp(+a)} \tag{13}$$

can be used. Figure 1 illustrates the binary modulo-2 addition with two inputs and the corresponding elements in the λ, L and Λ domain, respectively. An extension to more than two inputs is straightforward.

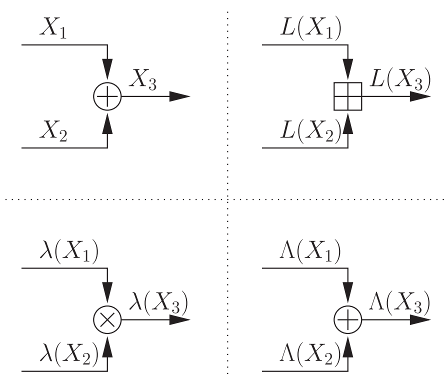

Figure 1: GF(2) addition and corresponding operations: λ (multiplication), L (box-plus) and Λ (addition).

3 The Turbo Principle in Decoding, Detection and Equalisation

The perhaps most prominent application of soft-output processing is the so-called *turbo principle* [13]. The turbo principle has successfully been applied in decoding (particularly in iterative decoding of parallel and serially concatenated codes, and low-density parity-check (LDPC) codes), detection, equalisation, interference suppression, combined source and channel decoding, and related applications.

In Figure 2, the turbo principle is illustrated for parallel concatenated codes (e.g., "Turbo codes" or block product codes). According to the weather problem, the outputs of the component decoders are combined so that only the novel information (called extrinsic information) is passed between the decoders. For the component decoders (DEC1 and DEC2), typically a-posteriori probability (APP) decoders (also called symbol-by-symbol MAP decoders) or simplifications thereof are used [14].

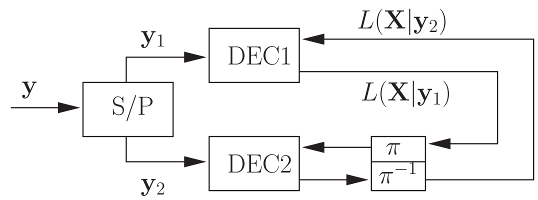

Figure 2: The turbo principle for parallel concatenated codes.

4 Soft-Simulation and Reliability-Based Adaptive Modulation

Let us consider the block diagram shown in Figure 3. In conventional Monte Carlo simulations, the bit error rate (BER) of a digital communication scheme is estimated by comparing the decoded (or detected) bits with the transmitted bits. If an APP decoder (or detector) is available, the magnitude of the LLR values can be used alternatively according to

$$P_b = \lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} \frac{1}{1+e^{|L_k|}} \tag{14}$$

in order to obtain an improved estimate of the BER given the same number of samples K [15, 16]. This technique has been dubbed *soft Monte Carlo simulation*.

Besides providing a better statistical significance of the simulation results, in soft Monte Carlo simulation the knowledge of the transmitted bits is not needed. This structural advantage may be used for adaptive modulation and channel coding schemes. The LLR values (or the corresponding a-posteriori probabilities) can directly be used as a performance measure of the quality of service (QoS). In

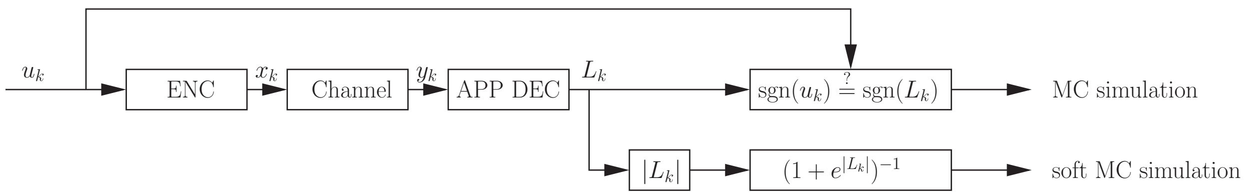

Figure 3: Conventional Monte Carlo simulation (top) and soft Monte Carlo simulation (bottom).

on-going research, LLR values are used for cross-layer optimisation.

5 Frame Synchronisation

During the time at which soft output algorithms were becoming firmly established in the coding community, the techniques were extended to other areas in communications in the hope of achieving similar performance improvements. Synchronisation covers a wide area, from symbol and frame timing to carrier phase and frequency offset estimation. The derivation of the Maximum Likelihood (ML) soft input frame synchronisation technique for data frames transmitted over Gaussian channels had been published by Massey in 1972 [17], and this approach showed an improvement over the naive solution that had been hitherto employed. Later work extended this to various fading environments, other modulation formats, carrier phase ambiguities, and to the situation where a single packet is transmitted within a time window [18]. In all cases the derivation of the optimal likelihood function led to the inclusion of *all available information*, such as the channel state or the presence of trellis encoded data where the trellis is terminated, and yielded further performance gains.

Frame synchronisation also lends itself to a form of soft output that can dramatically improve synchronisation reliability even further. Rather than selecting only the ML frame synchronisation solution a *list of frame or packet starting positions* can be generated that is sorted according to their likelihoods: The probability that the correct position is actually in this list increases dramatically as the length of the list grows. Assuming that the data itself is coded, and that errors can be reliably detected, a receiver can work though the list until it correctly decodes a packet or frame, with only a minimal increase in the average computation time. This soft output in the form of a list of candidate positions greatly reduces the computational burden of frame synchronisation algorithms that employ the side information from the starting and termination portions of trellis encoded data. By producing a short list (typically fewer than ten) based on the simple, random data case, the augmentation terms due to the starting and termination parts of the trellis need only be computed for these candidates. Such list-output synchronisers can work in concatenation, with the list lengths becoming shorter at each stage.

We conclude with an example of packet synchronisation where packets begin with a sync word of length L and carry 60 bits (protected by an error detecting code) and which are finally encoded by a rate 1/2, memory 5 convolutional code with trellis termination. The packets are BPSK modulated and transmitted over an AWGN channel with $10\log_{10}(E_s/N_0) = 2$ dB and have to be detected in a window that is 31 symbols longer than the total packet. The required sync word length (to obtain a frame detection rate of 10^{-3}) can be reduced from 21 to 4 compared to the simple correlation approaches by employing two list synchronisers with list lengths of 7 and 3 respectively; the first list being the soft input to the trellis-termination frame synchroniser and the second as input to the data decoder.

6 Soft-Location

An area of signal processing that is also profiting from advances in processing uncertain data is navigation, and in particular *sensor fusion* in localisation. From a structural point of view many data decoding problems and that of estimating the unknown location of a moving object are very similar. Both are estimation problems of a hidden (Markov) process: in the case of coding we want to estimate the state of the encoder (or multipath channel) at the receiver, given some noisy channel measurements. In navigation, our subject's movement can also be modelled as a Markov process, where the location and other variables such as speed and heading form the unknown state. The measurements are a noisy function of the state and come from one or more sensors, such as a compass, inertial sensors, satellite navigation receiver, etc.

Under certain assumptions, such as independently disturbed measurements and white measurement noise, such problems can be solved by the application of Bayesian filters: A family of related algorithms like the (extended) Kalman filter or particle filter. The 'soft' aspect covers both the definition of the measurement error model (soft-in) as well as the posterior distribution of the estimated location (soft-out). Navigation applications that draw on the soft output can more easily adapt their behaviour to the uncertainty in the location, by modifying route planning, for instance, or activating additional location sensors. When soft location is applied on mobile devices, with a changing configuration of sensors, suitable system designs have to be found that generalise the principle of a sensor to allow dynamic loading of the relevant measurement model and likelihood function (in software) [19].

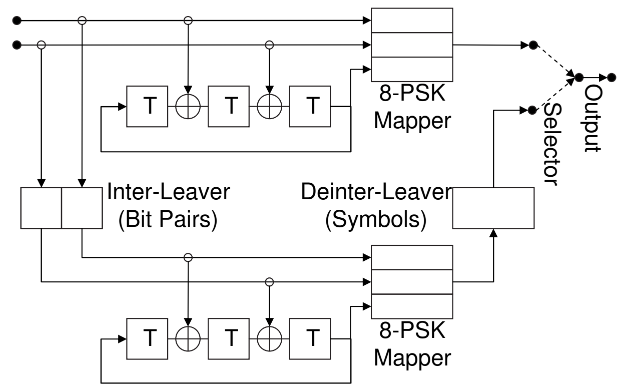

Figure 4: TTCM encoder using two rate 2/3 encoders and 8-PSK as an example.

7 TURBO-TCM

The decoding of Turbo Trellis Coded Modulation (TTCM) is another important application area, whose performance heavily depends on the use of soft outputs and the iteration principle.

In this construction, two Ungerboeck type of codes in combination with Trellis Coded Modulation (TCM) in their recursive systematic form are employed as component codes [20], similar to binary Turbo codes. Figure 4 shows an example applying two rate 2/3 convolutional codes and an 8-PSK signal mapper using Ungerboeck partitioning. The incoming bit stream is fed pairwise to the first encoder, where one additional parity bit is generated, and also after passing through an interleaver, working on bit pairs and mapping odd to odd and even to even positions, to the second encoder, where another parity bit is produced. In each case, both encoders are followed by a signal mapper that converts the two information and one parity bit into an 8-PSK symbol. The output of the bottom encoder/mapper is deinterleaved according to the inverse operation of the interleaver, and the selector is switched such that a symbol is chosen alternately from the upper and lower inputs. This ensures that at the input of the selector, the two information bits partly defining the symbol of both the upper and lower input are identical.

In an alternative approach, it is proposed to quadruplicate the signal set and transmit the parity bits from both encoders, which would lead in our example to the use of a 16-ary modulation set instead of 8-PSK [21]. As a consequence, an appropriate set partitioning has to be defined.

The decoding of each component code is typically done by means of the nonbinary symbol-by-symbol MAP algorithm. For that purpose the definition of log-likelihood values can be extended appropriately. Compared to binary Turbo codes two important differences have to be taken into account: (1) Since the systematic and parity bits are transmitted on the same symbol, the systematic and extrinsic information $(e\&s)$ can not be separated at the output of the MAP decoder; only the a-priori information a can be isolated. (2) Each component decoder alternately sees a symbol with a parity bit coming from its encoder and one with a parity bit from the other encoder in the sequence of received symbols. The appropriate iterative decoding principle is shown in Figure 5, which shows the decoding of one symbol y_k.

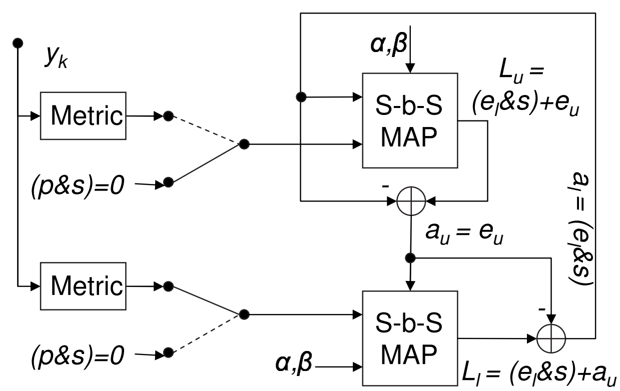

Figure 5: TTCM decoder principle.

Here, it is assumed that y_k comprises a parity bit from the lower encoder. Consequently, the lower decoder uses the metric value $(p\&s)$ of y_k and the a-priori information a_u from the upper encoder, when the logarithms of the a-posteriori probabilities $L_l = \log Pr(d_k = i|\mathbf{y}), i = 1 \dots 4,$

are calculated by the MAP algorithm $L_l = (e_l \& s) + a_u$. The information that is sent to the upper encoder as a-priori information a_l is generated by $a_l = L_l - a_u = (e_l \& s)$. It should be noted that the combination of extrinsic and systematic information is provided to the upper decoder. Since it "sees" a symbol with a parity bit from the lower encoder, a metric value $(p \& s) = 0$ (= ignored) is inserted in the MAP calculation at step k; only a_l is used. The output is $L_u = (e_l \& s) + e_u$. Removing the a-priori information, one obtains as extrinsic information $L_u - a_l = e_u = a_u$ that is provided to the lower decoder which ends one iteration.

8 Conclusions and Further Applications

In this paper we have sketched the development of soft-in and soft-out algorithms in coding and communications engineering. As receiver and system architectures became more elaborate, using concatenated coding schemes, source coding and channel equalisation to combat inter-symbol interference, it became necessary to address the best possible interface between different components of the receiver chain. The soft-in / soft-out principle is firmly routed in probability theory and is the basis for such receiver chains as well as iterative receivers. By adopting a logarithmic representation of the likelihood ratio numerical problems can be avoided and 'soft' operations at the bit level can be implemented by simple structures. New work is taking the soft output up to higher levels of the communications reference model, allowing for more effective cross-layer-optimisation: for example, routing metrics may be based on LLR values.

Communications technology is not the only area of research that has profited from these approaches. The communications receiver must typically perform a number of estimation tasks, and structurally similar problems exist in many domains, from speech and pattern recognition, image and sensor processing, to localisation. During the last decade or so, researchers from these fields have been drawing together and comparing their models and algorithms. McEliece, MacKay, and Cheng recognised that iterative Turbo decoding is 'just' loopy belief propagation in a Bayesian network with undirected cycles [22]. Fortunately for the coding community, application of this suboptimal algorithm works well in their context but fails in many others with differently structured networks or where the posterior probabilities of the hidden variable must be determined exactly. Another promising and related set of algorithms is based on Sequential Monte Carlo techniques and has been applied to communications problems such as channel estimation (e.g. [23] as an application of particle filtering) as well as in many other domains [24].

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Elke Offer was born in 1965 and received the Dipl-Ing. degree as well as the PhD degree in Electrical Engineering from the University of Munich/Germany in 1989 and 1996, respectively. From 1990 to 1995 she was a scientific employee of the German Aerospace Centre (DLR) and from 1997 to 2003 she had a postdoctoral position at the Institute of Communications Engineering, Munich University of Technology. Here she held lectures concerning the fundamentals of communication theory and channel coding. Her research interest included channel coding with emphasis on iterative decoding techniques. Since 2003 she has been working as patent examiner in the area of channel coding at the European Patent Office, Munich.

Thomas Woerz was born in 1961 and received a Diploma in 1988 from the Technical University of Stuttgart / Germany, a PhD degree in 1995 in Electrical Engineering from the University of Munich / Germany, respectively. He joined the Institute for Communications Technology at the German Aerospace Centre (DLR) as research staff member in 1988. Thomas was one of the cofounders of AUDENS ACT Consulting GmbH in 1998, which offers technical consulting in the area of satellite communications and navigation. His expertise comprises analysis and modelling of mobile satellite and terrestrial wireless channels, signal structures and corresponding receiver design, including channel estimation, equalisation, synchronisation, demodulation and decoding, for MF-TDM(A) and spread spectrum/CDM(A) systems covering applications like point-to-multipoint communication (e.g. INTELSAT standards), Digital Audio Broadcasting (DAB), Digital Video Broadcasting (DVB), UMTS, and satellite navigation systems.